1 **Supplementary information to the following publication:** Griffith, D.M., Byrd, K.B.,

2 Anderegg, L.D.L., Yacoub, R., Gatziolis, D., Roberts, D., Nemani, R.R. (2022) Capturing

patterns of evolutionary relatedness with reflectance spectra to model and monitor biodiversity. $\begin{array}{c} 3 \\ 4 \\ 5 \end{array}$

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Figure S1. Minimum Noise Fraction representation (bands 2, 3, and 4 as RGB) of the Southern

Sierra Nevada Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) hyperspectral data.

This visualization approach illustrates the variation present in the highly multi-dimensional

spectral dataset. Forest Inventory and Analysis (FIA) plot data are included in this figure

(locations for figure are spatially fuzzed following FIA protocol, but exact plot locations were

 used in analysis). Notably, 'banding effects' due to influences such as sun-angle effects are highly noticeable in the spectral data along each flight line. We discuss the impact of these

- artifacts for our study and remote sensing in the Discussion.
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 Figure S2. Results of K-means clustering of spectra. Spectral Clusters 8 and 11 are associated with agricultural activity around Fresno, CA, and intersected 69 and 28 vegetations plots

- respectively (they were assigned two shades of orange). Spectral Clusters 3 and 4 had 99 and 274
- plots. Spectral Clusters 9, 10, 13, 15 had 222, 35, 260, and 165 plots, respectively. Sun-angle
- impacts are noticeable and discussed in text.
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Figure S3. Rank abundance curves for vegetation plot data in each of 8 spectral clusters. The 44 vegetation data come from Vegbank, VegCamp, and FIA.

NLCD Cover Change

 $\frac{45}{46}$ ⁴⁶ Figure S4. Frequency of original dataset in each land cover change category from years 2000 to 47 2019.

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Figure S5. Selection of CDA (Canonical Discriminant Analysis) axes for dimension reduction.

This screeplot represents the cumulative variance explained in the spectral data based on the

number of CDA axes. The axes in CDA are optimized for emphasizing spectral difference

 among the dominant plant species in each represented spectrum based on vegetation data, which differs from more standard ordination approaches. As a result, the screeplot is not as steep as

many other methods of ordination as the focus is not on explaining spectral variation with few

axes, but instead on distinguishing plants. We selected the axes that together explained two-

thirds of the variation in spectral data based on the number of bands selected in Meerdink et al

(2019) and to enable data processing to occur in a reasonable time frame.

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 Figure S6. Non-metric Multidimensional Scaling ordination results. On the left panel, red text shows the Operational Taxonomic Units (OTU) positions in in multivariate space, whereas black

 text indicates the position of Spectral Clusters in multivariate space (e.g., "s.9" is Spectral Cluster #9).

- Supplementary Methods S1.
- We considered several approaches for generating Lineage Functional Types. First, we considered
- a simple age-based approach that cut the phylogeny into different sized lineages using an age
- threshold (Fig. S7). However, this approach was unsatisfactory because it was biased towards the
- basal grade and had no potential for explicitly including abundance data or for vegetation traits
- that should be balanced in the generation of LFTs. Alternatively, we tried the KSI method from
- Cornwell et al., (2014) which searches for lineages with distinct functional synapomorphies.
- While a modification of this approach might be a major improvement in the future, the result we received with PCA axes as substitutes for traits didn't reflect the vegetation patterns we see in
- the Indicator Species Analysis and it selected lineages that were most unique (leaving many
- species unselected) and not balanced across the tree. Fig S8 illustrates the poor performance of
- this method as compared to the simple spectrally informed LFT generation approach we used.
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Figure S7. Log lineages over time, used for splitting the tree based on age. These cuts were

- completed on the full tree which comprises the 1572 species in our study.
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Supplementary Information Griffith *et al* (2022)

103 Figure S8. PLS-DA classification Kappa in black and random forest Out of Bag (OOB) error in red for classifications based on different numbers of cuts to phylogeny. red for classifications based on different numbers of cuts to phylogeny.

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Figure S9. Spatial visualization of Support Vector Machine classification error based on the FIA

113 data. FIA plots shown in the figure are fuzzed-and-swapped but the spatial statistics were

114 performed using the actual plot coordinates. We used the Join-Count Statistic in the spdep R

- 115 package to show that the classification errors are not clustered ($p = 0.43$).
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Figure S10. Mean Phylogenetic Distance (MPD) for each spectral cluster overlayed on null distributions generated by simulating community assembly from the phylogeny in Fig. 2 999

times. Over half of the naïve spectral clusters represented indicator species that were more

phylogenetically related than expected, and only two of the eight clusters were phylogenetically

'over dispersed,' or less related than expected. We calculated MPD using the R packages 'ape'

and 'picante' – MPD is simply the mean of the distances of all the species in a community along

the edges of the evolutionary tree. To generate null models we simulated the assembly of

127 communities into each spectral cluster ($n = 999$) and calculated the MPD in each cluster (Paradis

et al., 2004; Kembel et al., 2010). We then compared the actual MPD for each cluster with the

simulated null distribution.